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QUALITY ASSESSMENT OF POWER SYSTEM USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In recent years Artificial Intelligence has been proposed as an alternative tool to provide quick solutions to certain difficult power system problems. With intelligent systems, such as ANN, the available information regarding the power system can be stored and retrieved as a part of new solution process. ANN computing may require larger time for off line training but is capable of giving instant response for a given condition and hence, is suitable for on-line applications.

This paper describes ANN base technique for obtaining the quality of interconnected power system. Desired level of voltage has been maintained using back propagation algorithm base network, which is trained to represent the system as ANN model. The well-trained model can use to predict the quality and the losses of the power system. This trained model can also predict the behavior of the network as load increase.

KEYWORDS: Artificial Intelligence, ANN, Alternative Tool, Off Line Training, Quality of Interconnected Power System

INTRODUCTION

There has been a remarkable progress in the development of software and hardware for the design and analysis of power systems. However, much still depends on judgment of human experts. Experienced planning and design personnel make efficient and viable decisions on the basis of their comprehensive experience and the knowledge of prevailing circumstances.

This paper mainly gives the description of the concept of Artificial Neural Network in the field of assessment of power system. The IEEE-30 bus model has been taken for the analysis of voltage, phase angle and losses variation. Simulated model has been trained for the production of quality of load flow.

Artificial Intelligence based Demand Side Management has been developed by I.E.Hopley et al [1] and A.S.Zadgaokkar [2] to support energy management in power system during abnormal situations. Hoyong Kim et al [3] and E.A. Mohamed [4] suggested Artificial Neural Network based feeder reconfiguration for loss reduction in distribution systems.

ANN Models have been suggested to give direct and accurate results nearly instantly for the sample IEEE 30-Bus power systems. The study includes bus voltage distribution and phase angle.

ANN FOR LOAD FLOW SOLUTION

The conventional solution techniques use series mode of iterative calculations that makes it more time consuming. The strong parallel processing capability of Artificial Neural Network is therefore applied to solve the load flow problem. The ANN technique is totally different from the conventional techniques. The ANN model does not at all represent the inherent intricate mathematical non-linear relationships among the input-output parameters constituting the power system

equations. The proposed ANN model mainly has been developed to analyze the power system equations in their decoupled form. The trained ANN model carrying out the fast estimation of voltage, phase angle, losses for contingency analysis and security assessment by using entropy as the input information.

Back Propagation technique is more popular for off line applications. The feed Forward Neural Nets (FFNN) have been found to be more effective than Radial Basis Function Nets (RBFN).

In Figure 1.1(b). let the input for jth for node at the hidden layer II be net and the output of hidden layer I be O_i^1, then

$$\text{net}_j^{II} = \sum w_{ji} O_i^l \tag{1}$$

where i = 1,2 … p, for hidden layer I

and j = 1, 2. . .q, for hidden layer II.

Figure 1(a) shows the most Common activation (transfer) function - A Sigmoid Function'. It is described as

$$f(a) = 1/\left[1 + \exp^{(-a)}\right] \tag{2}$$

For jth node of hidden layer II, the effective input is

$$a = \left[\left\{\text{net}_j^{II} + 0_j^{II}\right\}/0_0\right] \tag{3}$$

Where 0_0 is the shape modifier of the activation function. It decides the abruptness of transition.

The output jth node, therefore, is

$$O_j^{II} = =1 /[l+\exp\{\sim(\text{net}^{11}{}_1+0^{11}{}_1)/0_0\}] \tag{4}$$

Artificial Neural Network is an advanced and fast upcoming Artificial Intelligence technique finding applications in various fields of Engineering including Power System Engineering [6]

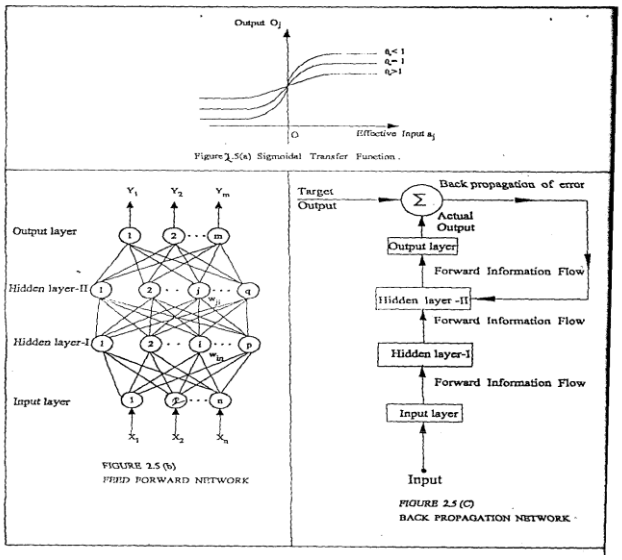

Figure 1: (a) Sigmoid Transfer Function, (b) Feed Forward Network, (c) Back Propagation Network

STEEPEST DESCENT RULE OF BACK PROPAGATION

The actual output is Y_m and the target output is t_m, then for obtaining the minimization of error function, the sum-squared error is given by

$$E = ½ \sum(t_m - Y_m)^2 \tag{5}$$

The searching of solution is done along the negative of the gradient Suppose the solution vector $w_{ji}^{(k+1)}$ minimizes the criterion function $w_{ji}^{(k)}$, starting with an arbitrarily chosen vector w_{ji}, the procedure finds the solution vector by iteratively applying the following algorithm until convergence.

$$w_{ji}^{(k+1)} = w_{ji}^{(k)} - \eta(k)\, \delta_j\, w_{ji}^{(k)} \tag{6}$$

Where subscript ‘k’ denotes the k^{th} iteration. ‘ η ’ is a positive scale factor that sets up the step size and ‘ δ ’ is the error gradient operator.

For the output layer,

$$\delta_m = Y_m(1 - Y_m)\ (t_m - Y_m) \tag{7}$$

For hidden layer,

$$\delta_i = O_i^{(k)}(1 - O_i^{(k)}) \sum \eta^{(k)} \delta_j^{(k+1)} O_i^{(k)} \tag{8}$$

Weight Correction

The weight is corrected by tracing the error backward as

$$w_{ji}^{(k+1)} = w_{ji}^{(k)} - \Delta w_{ji}^{(k)} \tag{9}$$

and $\Delta w_{ji}^{(k)} = \eta^k \delta_j^{(k+1)}\ O_i^{(k)}$ (10)

‘η’ is a trial independent learning rate (0 < η < I) and ‘δ’ is the error gradient. A momentum is sometimes added for faster convergence as follows.

$$w_{ji}^{(k+1)} = w_{ji}^{(k)} \eta^k\ \delta_j^{(k+1)} w_{ji} + \alpha_j \left[w_{ji}^{(k)} - w_{ji}^{(k-1)} \right] \tag{11}$$

where ‘ α ’ is the momentum constant ($0 < \alpha < 1$).

The connection weights between the nodes of all successive layers are updated in all the iterations. The thresholds values are also modified considering them as connections variable weight connected to fictitious nodes of previous layer having unity output.

One of the basic problems in most of the power system studies is to find the voltage magnitude and the voltage angles at its different buses that meet the given schedule of the load and the generation within the prescribed constraints. Ever increasing size of the power systems necessitates excessive memory size and prohibitive computational time for assessment of the current status of power lines on computers.

This model containing the 100 neurons in the first layer, seventy five in second and 30 neurons in the output layers. Transfer functions are sigmoid and pure linear for hidden and the output layer. There are two hidden layers. Selected neuron model is as follows,

```
p= [ ];

t= [ ];

net=newff(minmax(p),[100,75,30],{'tansig','tansig','purelin'},'trainrp');

net.trainParam.show = 20;

net.trainParam.lr = 0.005;

net.trainParam.epochs = 450;

net.trainParam.goal = 1e-5;

[net,tr]=train (net,p,t);

a = sim(net,p)
```

Training sample given to the model, as training accomplishes the model is ready for the test procedure. Result has been checked with test inputs. It is found that the results are very near to the calculated objects. Table given below contains the calculated outputs and model prediction. These observations are as follows.

Table 1

Voltage, Phase Angle and Loss Calculation								
Losses					Voltage and Phase Angle			
	Calculated Loss		Ann Output		Calculated O/P		Ann O/P	
Bus No	Mw	Mvar	Mw	Mvar	V Perunit	Ph Ang	V Perunit	Ph Ang
1	5.461	10.517	5.4634	10.5161	1.06	0	1.06	0
2	5.461	10.517	5.4618	10.5115	1.043	-5.496	1.043	-5.496
3	2.807	7.079	2.8067	7.0766	1	-8.002	1	-8.002
4	1.106	0.519	1.1059	0.5222	1.06	-9.695	1.06	-9.695
5	2.995	8.178	2.9965	8.1743	1.01	-14.98	1.01	-14.98
6	2.047	2.263	2.0472	2.267	1	-11.396	1	-11.396
7	0.151	-1.687	0.1507	-1.6879	1	-13.149	1	-13.149
8	0.103	-0.558	0.1033	-0.5596	1.01	-12.114	1.01	-12.114
9	0	1.592	-0.0004	1.5946	1	-14.432	1	-14.432
10	0.11	0.236	0.1099	0.2396	1	-16.024	1	-16.024
11	0	0.461	-0.0002	0.4663	1.082	-14.432	1.082	-14.432
12	0.217	0.428	0.2175	0.4247	1	-15.301	1	-15.301
13	0	0.132	0.0002	0.1314	1.071	-15.3	1.071	-15.3
14	0.074	0.155	0.0742	0.1575	1	-16.19	1	-16.19
15	0.217	0.428	0.2172	0.4297	1	-16.276	1	-16.276
16	0.053	0.112	0.0539	0.1071	1	-15.879	1	-15.879
17	0.012	0.027	0.0111	0.0309	1	-16.187	1	-16.187
18	0.039	0.0795	0.039	0.0764	1	-16.881	1	-16.881
19	0.017	0.035	0.0173	0.0339	1	-17.049	1	-17.049
20	0.081	0.18	0.0825	0.1785	1	-16.851	1	-16.851
21	0.11	0.236	0.107	0.2447	1	-16.468	1	-16.468
22	0.052	0.107	0.0525	0.1077	1	-16.455	1	-16.455
23	0.031	0.064	0.0303	0.0659	1	-16.66	1	-16.66
24	0.043	0.67	0.043	0.6621	1	-16.829	1	-16.829
25	0.044	0.066	0.0444	0.0705	1	-16.423	1	-16.423

Table 1: Contd.,

26	0.044	0.066	0.0439	0.0714	1	-16.835	1	-16.835
27	0.162	0.304	0.1621	0.2971	1	-16.913	1	-16.913
28	0.06	-13.085	0.0619	-13.083	1	-12.056	1	-12.056
29	0.086	0.162	0.0858	0.166	1	-17.133	1	-17.133
30	0.162	0.304	0.1613	0.3129	1	-18.016	1	-18.016

OBSERVATION AND CONCLUSIONS

The work on “Quality Assessment of Power system Using Artificial Neural Network” was mainly focused at determining the voltages, phase angle, and losses of the buses system. Various ANN models were developed and the results obtained were compared with that obtained by conventional technique. The ANN Model gave the most satisfactory results. The same model, with the corresponding input output information was then applied on a sample IEEE 30-Bus power system.

The comparison of the performance of the proposed new technique using ANN with that of the conventional techniques was based on the following factors.

1. Computational Time. **2.** Accuracy, and **3**.Robustness and Generalization.

The results obtained showed that the computational time is nearly instantaneous. The results are sufficiently accurate. These two factors establish the viability and the acceptability of the applications of Artificial Neural Network for assessing the power line status. The input and output nodes of various ANN Models were defined as per the need of the problem. With the advent of the Neural Network Toolbox, the solution became very fast. A model proved worthy for 30-Bus system. This shows that, in general, a tested ANN can be applied to obtain similar solutions for any big size problem provided adequate data is available for training the network. For a given power system the effects of various selected parameters on selected quantities can be assessed easily and quickly using ANN.

The suggested ANN based methods of assessment of power line operation gave instantaneous results with sufficient accuracy. ANN technique was found to have additional computational advantages such as speed, robustness, stability and flexibility of operation. The results reveal the status assessment of power lined using ANN is of great use and importance to the power system engineers.

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